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# Evaluating Pretrained YOLO11s Vehicle Detection Under Daylight and Simulated Nighttime Conditions Using Lightweight Image Enhancement

**Marwa K. Hasan[1*], Lana O. Alhamawndi[2], Maroa Essam Baker[3]**

[1,2,3]Technical Engineering College - Kirkuk, Northern Technical University, Kirkuk, 36001, Iraq

**ABSTRACT:** Vehicle detection is an important perception task in Intelligent Transportation Systems (ITS) and Advanced Driver Assistance Systems (ADAS), and the performance under different illumination conditions still remains as an important challenge. The current deep-learning object detectors perform well under daylight conditions, while the detection behavior may be degraded in nighttime and low-light conditions due to low contrast and limited object visibility. This paper introduces a lightweight and reproducible framework for evaluating the pre-trained YOLO11s object detector in daylight and simulated night-time scenarios without any further retraining of the model. A typical road-scene frame from an actual daytime driving video was used to produce a corresponding simulated nighttime image with the same road geometry, vehicle locations, and camera viewpoint. The vehicle detection was preceded by enhancing the nighttime image using Contrast Limited Adaptive Histogram Equalization (CLAHE) and Gamma Correction. Detection behavior was evaluated by the number of detected vehicles, confidence-score statistics, confidence-level distribution, confidence ranking, scatter visualization, confidence-weighted heatmaps, and exploratory Pearson correlation analysis. The experimental results showed that YOLO11s detected 10 vehicles during daylight conditions and 3 vehicles under simulated nighttime conditions, which is about 70% less detections under reduced illumination. This is a decrease, but the most visually prominent vehicle still had a high confidence score in both conditions, while a number of weaker detections, including a dark-colored vehicle, were lost in the simulated nighttime scene. The proposed framework provides a simple and reproducible way to study the effect of illumination on the detection behavior of pretrained YOLO11s and highlights the need for further validation on larger datasets and real nighttime driving scenes.

**KEYWORDS: Vehicle Detection,YOLO11s, Intelligent Transportation Systems, Advanced Driver Assistance Systems, Low-*Light Vision, Image Enhancement, CLAHE, Gamma Correction.***

## I. INTRODUCTION

Advanced driver assistance systems (ADAS) and intelligent transportation systems (ITS) have become important technologies to improve road safety, reduce traffic accidents, and support higher levels of driving automation. They use computer vision extensively to sense the surrounding environment and support real-time decision-making. As one of the main perception tasks for collision avoidance, adaptive cruise control, traffic monitoring, and autonomous navigation, vehicle detection is an important research topic in intelligent transportation systems [1]–[4].

During the last ten years, deep learning has developed rapidly and considerably changed object detection. Specifically, the You Only Look Once (YOLO) family has become one of the most popular object-detection frameworks because of its advantageous compromise between detection precision, inference speed, and computational cost [5]–[7]. Continuous improvements in successive YOLO architectures have enhanced their ability to detect vehicles in complex road environments, making them attractive for autonomous-driving and ADAS applications [7]–[9].

However, illumination variation remains a major challenge for vision-based vehicle detection despite these advances. Models that perform effectively under daylight conditions can degrade significantly under nighttime or low-light conditions because of reduced contrast, limited visibility, shadows, and sensor noise [10]–[13]. These conditions may reduce detection confidence and increase missed detections, especially for small, distant, dark, or poorly illuminated vehicles. Recent studies have also highlighted the challenges associated with vehicle detection under nighttime and adverse-visibility conditions [14]–[16]. Thus, the effect of illumination on vehicle-detection behavior remains an important issue in autonomous-driving perception [13]–[16].

Several image-enhancement methods have been investigated to address low-light visibility problems as preprocessing steps before object detection. Conventional approaches such as Gamma Correction and Contrast Limited Adaptive Histogram Equalization (CLAHE) can improve image brightness and local contrast with relatively low computational complexity. In contrast, recent deep-learning-based enhancement methods can provide more sophisticated image restoration but generally require additional models, training data, and computational resources [10]–[12], [14], [17]. Lightweight preprocessing methods therefore remain attractive for applications where simple implementation and limited computational requirements are important.

In parallel with vehicle detection, lane detection represents another fundamental perception task in intelligent transportation applications. Both traditional image-processing methods and deep-learning techniques have been investigated to improve lane localization under challenging environmental conditions [18], [19]. In our previous work, a lightweight training-free lane-detection framework was developed to address day–night illumination changes on CPU-based platforms [20]. The results demonstrated the potential of carefully designed image-processing procedures for improving visual perception without requiring additional neural-network training. This previous investigation motivated the extension of lightweight illumination-aware preprocessing from lane perception to vehicle detection.

Motivated by these observations, the present study evaluates the behavior of the pretrained YOLO11s object detector under daylight and simulated nighttime conditions without additional model retraining. A representative daytime road-scene frame extracted from a real driving video is used to generate a corresponding simulated nighttime image while preserving the same road geometry, vehicle locations, and camera viewpoint. Before vehicle detection, the simulated nighttime image is enhanced using lightweight CLAHE and Gamma Correction. The inference settings for YOLO11s remain the same under both illumination conditions to allow a controlled comparison.

Qualitative inspection of the detection results is complemented by descriptive confidence statistics, confidence-level analysis, confidence ranking, scatter visualization, confidence-weighted spatial heatmaps, and exploratory Pearson correlation analysis. These complementary analyses provide further insight into the effect of illumination on the number of detected vehicles, detection confidence, apparent vehicle size, and spatial detection characteristics. Hence, the main contribution of this work is a simple and reproducible framework for studying the behavior of pretrained YOLO11s under controlled daylight and simulated nighttime conditions without any modification or retraining of the original detector.

## II. METHODOLOGY

### *A. Overall Framework*

Here, we propose an image-based vehicle detection framework to evaluate the performance of the pretrained YOLO11s object detector under daylight and simulated nighttime illumination conditions. As the main experimental image, a typical road scene frame was extracted from a real daytime driving video.

A corresponding simulated nighttime image was derived from the same daylight frame. This paired-image strategy preserves the road geometry, camera's viewpoint, vehicle locations and the scene composition, only changing the illumination condition. The effect of reduced illumination can be evaluated in this way without the introduction of geometric or positional differences between the scenes compared.

The proposed framework begins with extracting a representative frame from a real daytime road scene. Then, a simulated nighttime version of the same frame is created with the same road geometry, camera viewpoint, vehicle locations and scene composition as the original. Then the simulated night-time image is processed with light-weight low-light enhancement techniques and vehicle detection is performed using the pretrained YOLO11s model. The detection results under daylight and simulated night conditions are finally evaluated using statistical and visualization analyzes. In an effort to make a fair and consistent comparison, the same detector settings are used for both illumination conditions.

### *B. Image Preprocessing and Nighttime Simulation*

The chosen daylight road-scene image was converted into a simulated nighttime scene by reducing the overall image illumination, but retaining the structural and spatial features of the original road scene. No geometric transformations, no cropping or repositioning of vehicles were involved in this process. Hence, the daylight image and the corresponding simulated night image represent the same road scene under two different illumination conditions.

This pairing of images in a controlled fashion makes it possible to treat illumination as the primary experimental variable, and to make a direct comparison of the detection behavior of YOLO11s under daylight and reduced-light conditions.

To enhance the visibility in a simulated low-light condition, the nighttime image was enhanced through a lightweight pre-processing procedure consisting of a combination of CLAHE and Gamma Correction. The LAB color space was used to apply CLAHE on the luminance channel with a clip limit of 1.8 and a tile-grid size of $8 \times 8$ pixels. This method enhances local contrast without over-enhancing the noise.

Then Gamma Correction ($\gamma = 0.75$) was applied to improve the visibility of dark image regions and road details. The combination of CLAHE and Gamma Correction was chosen since these techniques have a relatively low computational complexity and do not require additional neural-network training.

### *C. Vehicle Detection Using YOLO11s*

Vehicle detection was performed using the YOLO11s pre-trained object detection model implemented in the Ultralytics framework. The pretrained yolo11s.pt weights were used as is without any further fine-tuning or retraining since the model was originally trained on the COCO dataset.

The detector was set to keep 4 object categories related to vehicles: car, truck, bus, and motorcycle. The vehicle level analysis did not include other detected classes of objects.

To compare daylight and simulated nighttime conditions fairly, we used the same YOLO11s inference parameters for both images. Table 1 summarizes the adopted configuration.

**Table 1.** Inference parameters of YOLO11s

| Parameter | Value |
|---|---|
| Model | YOLO11s |
| Weights | yolo11s.pt |
| Input size | 960 × 960 pixels |
| Confidence threshold | 0.10 |
| IoU threshold | 0.50 |
| Maximum detections | 100 |
| NMS | Class-agnostic |
| Vehicle classes | Car, truck, bus, motorcycle |

Bounding-box coordinates and the corresponding confidence score of each detected vehicle were directly extracted from the YOLO11s output. The normalized bounding-box area was calculated as:

$$A_n = \frac{(x_2 - x_1)(y_2 - y_1)}{WH} \tag{1}$$

where $x_1, y_1, x_2$, and $y_2$ are the bounding-box coordinates, and W, H are the image width and height respectively.

Also, the center position of each detected vehicle was extracted from its bounding box and normalized according to the image sizes. These measures were used for the subsequent statistical analysis.

### *D. Statistical and Visualization Analysis*

The results of vehicle detection from the daylight image and the corresponding simulated nighttime image were analyzed using descriptive statistics and visualization techniques. The analysis included total number of detected vehicles, mean, median, min, and max confidence scores, confidence score distribution, confidence ranking, and confidence level distribution.

The average detection confidence was calculated by:

$$\bar{C} = \frac{1}{N}\sum_{i=1}^{N} C_i \tag{2}$$

where $C_i$ denotes the confidence score of the $i$-th detected vehicle and $N$ represents the total number of detections. Detections were categorized for descriptive comparison into low confidence (0.10–0.39), medium confidence (0.40–0.79), and high confidence (≥ 0.80). These categories were used to show the distribution of strong and weak detections in the two illumination conditions.

In the confidence-ranking analysis, we ranked the confidence scores from highest to lowest to show the transition from the strongest to the weakest detections.

We also generated a confidence-weighted heatmap to visualize the spatial distribution of vehicle detections. Each detected vehicle contributed to the heatmap based on its spatial location and its associated confidence score, with detections with higher confidence scores eliciting stronger responses.

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Moreover, Pearson correlation analysis was employed as an exploratory tool to explore the relationships between detection confidence, normalized bounding-box area, horizontal position, and vertical position. The resulting correlation matrices provide additional insight into potential relationships between apparent vehicle size, spatial location, and detection confidence. Given the detection of only three vehicles under the simulated nighttime condition, the respective correlation results were interpreted with caution and considered to be exploratory rather than statistically conclusive.

### *E. Experimental Environment*

The proposed framework has been coded in Python with Jupyter Notebook. Vehicle detection and image preprocessing were done using the Ultralytics, PyTorch, OpenCV, NumPy and Pandas libraries, and the suitable Python visualization tools were used to generate the statistical figures and heatmaps.

The same parameters for preprocessing, vehicle categories, image dimensions, confidence threshold, IoU threshold, and YOLO11s inference were used for the daytime and simulated nighttime images to ensure consistency in the experiments.

If a GPU with CUDA was available, it was used; otherwise, YOLO11s inference was done on the CPU. The same computational and inference settings were used for all experiments, so that the differences in detection behavior are mainly due to changes in illumination and not due to differences in detector configuration.

## III. RESULTS AND DISCUSSION

The proposed vehicle detection framework based on YOLO11s was tested under daylight and simulated nighttime illumination conditions in an effort to investigate the effect of reduced illumination on the vehicle detection behavior. The analysis consisted of qualitative visual and confidence based statistical measures of changes in number, confidence, and spatial characteristics of the detected vehicles.

The original road scene in daylight is shown in Fig. 1(a), and the corresponding YOLO11s detection results are shown in Fig. 1(b). Under daylight conditions, the detector detected multiple vehicles at various locations of the road scene, including both visually salient and relatively small distant vehicles. Fig. 1(c) shows a confidence-weighted heatmap of the spatial distribution of the detection responses, where stronger responses correspond to vehicles with larger apparent image areas and higher confidence scores.

The corresponding low-light road scene under simulated night conditions is shown in Fig. 1(d), and the YOLO11s detection result is shown in Fig. 1(e). A significant decrease of detected vehicles can be observed compared to the daylight condition. However, the most visually conspicuous vehicles were still detectable. A notable failure case was observed for a dark-colored vehicle which was detected in the day time but missed under the simulated nighttime condition. This observation shows that the reduction in luminance and the lower contrast between object and background can have a significant effect on the detectability of dark vehicles, even if the road geometry and the positions of the vehicles are kept the same. The confidence-weighted heatmap in Fig. 1(f) also indicates that the other detection responses concentrate on the most visually distinguishable vehicles.

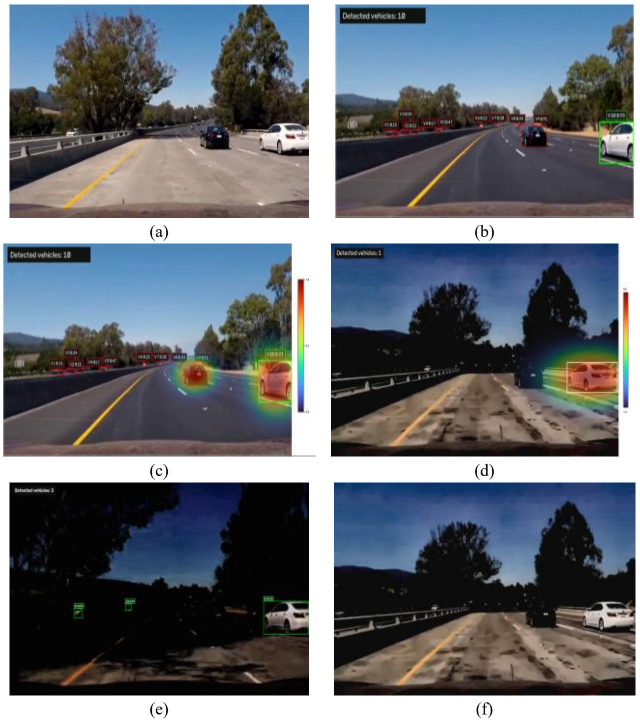


**Fig. 1.** Vehicle detection in daylight and nighttime simulation. (a) Original daylight image. (b) Detection results of YOLO11s in daylight condition. (c) Confidence weighted heatmap of daylight detection. (d) Simulated image of nighttime. (e) Detection results of YOLO11s under simulated nighttime conditions. (f) Confidence weighted heatmap for nighttime detection.

Fig. 2 presents the total number of detected vehicles for both illumination conditions for a quantitative comparison. YOLO11s was able to detect 10 vehicles under daylight conditions and 3 vehicles under simulated nighttime conditions, a reduction of ~70% in the number of detections. The considerable effect of the illumination degradation on the vehicle visibility is shown in this result. Specifically, vehicles with lower visual contrast or smaller apparent size were more likely to be missed under the simulated nighttime condition.

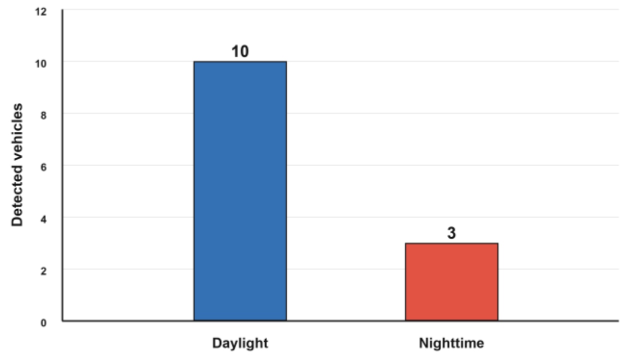


**Fig. 2.** Vehicles detected in daylight and simulated nighttime conditions.

Fig. 3 summarizes the statistical characteristics of the confidence scores. In daylight conditions, the mean confidence score was about 0.38, the median was about 0.23, the minimum was about 0.15, and the maximum was about 0.93. The values obtained under simulated nighttime conditions were approximately 0.47, 0.33, 0.17 and 0.92.

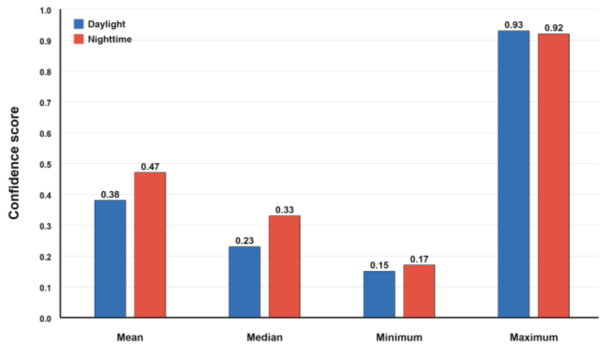


**Fig. 3.** Detection confidence scores for daylight and simulated night-time conditions, statistically compared.

Although the average confidence was numerically higher in the nighttime condition, this should not be taken to indicate improved overall detection performance. At night, only three vehicles could be detected, and the high confidence of one prominent vehicle increased the average value. However, the daylight condition resulted in a larger and more diverse set of detections, including a number of lower-confidence vehicles, which brought down the overall mean. It implies that the highest confidence values are similar, meaning that the most salient vehicle to the eye was detected with similar confidence in both scenarios.

The detected vehicles are categorized into high-, medium-, and low-confidence in Fig. 4. Under daylight conditions 2 high confidence, 1 medium confidence and 7 low confidence detections were obtained. Under simulated night conditions, the distribution was reduced to 1 high-confidence and 2 low-confidence detections, with no medium-confidence detections. These results show that reduced illumination decreases not only the total number of detections but also removes some weaker detections that are still detectable in daylight. Meanwhile, the top detection was relatively insensitive to illumination degradation.

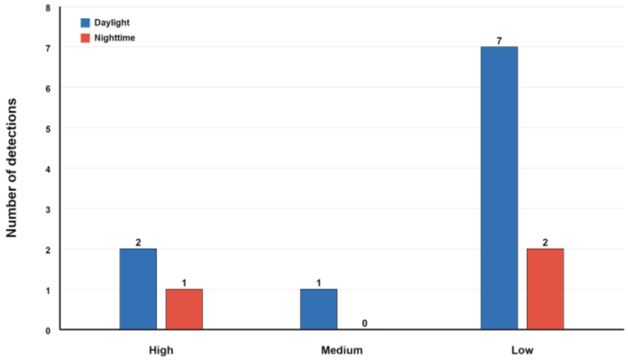


**Fig. 4.** Vehicle detection distribution across confidence levels in daylight and simulated nighttime conditions.

Fig. 5 depicts the confidence scores after sorting them in descending order of detection rank. The confidence values under daylight conditions gradually decrease from the strongest to the weakest detections, indicating a wider range of detectable vehicles. However, the simulated nighttime condition only has three detections with the confidence decreasing rapidly from the highest confidence detection to the two remaining detections. This difference shows that the number of detections kept over the selected confidence threshold is significantly reduced by the degradation of illumination.

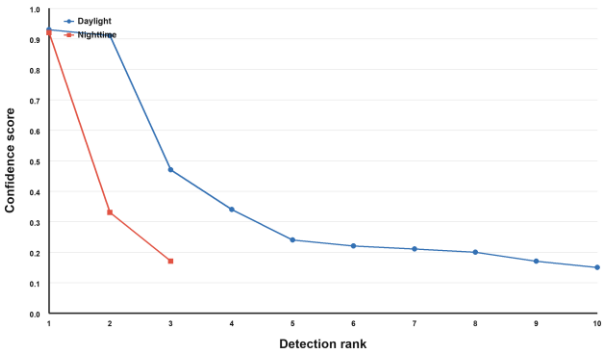


**Fig. 5.** Confidence scores in descending order for daylight and simulated nighttime conditions.

Fig. 6 shows a different view of the individual confidence scores as a scatterplot. This resulted in more widely distributed Daylight detections, and more vehicles at different confidence levels were detected. In contrast, the simulated nighttime condition has only 3 observations, which makes it a much sparser distribution. The vertical mean markers are mean confidence values of ~0.38 for daylight and ~0.47 for simulated nighttime. As stated before, the higher mean at nighttime is due to the small number and composition of the remaining detections and thus should not be taken as better performance at nighttime.

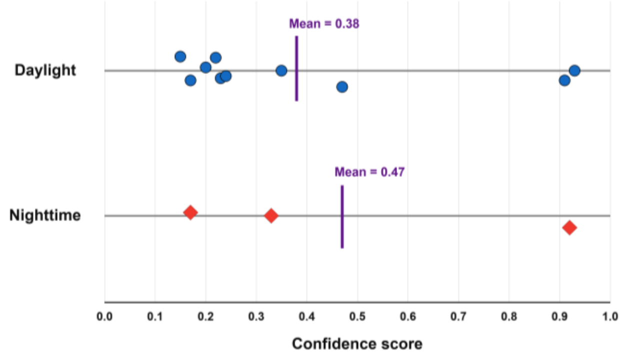


**Fig. 6.** Individual vehicle-detection confidence score distributions for daylight and simulated nighttime conditions, with mean confidence values shown.

To study the relationships between the extracted detection features, Pearson correlation analysis was performed using confidence score, normalized bounding-box area, normalized horizontal position, and normalized vertical position. The resulting matrices are shown in Fig. 7. The analysis under daylight conditions reveals positive associations between confidence and normalized bounding-box area, indicating that vehicles that occupy larger regions of the image generally tended to receive higher confidence scores.

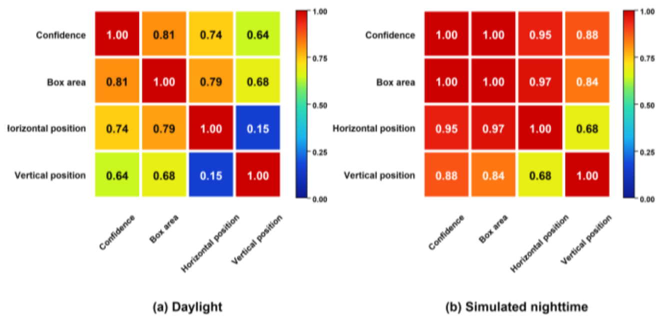


**Fig. 7.** Pearson correlation heatmaps of vehicle detection characteristic during daylight and simulated nighttime.

In the simulated night-time matrix, there are also numerically strong correlations between several variables. However, these relationships should be interpreted with caution as the nighttime analysis is based on only three detected vehicles. Because there are so few observations, any single detection can have a large effect on the correlation coefficients calculated. So, the night-time correlation matrix is an exploratory visualization, not a statistically definitive proof. However, the observed pattern is consistent with the qualitative results, where the most visually salient vehicles were more likely to be detected under reduced illumination.

The experimental results show a clear degradation of the detection behavior of YOLO11s when the illumination is lowered. In the daylight conditions, a much larger number of vehicles could be seen. In the simulated nighttime conditions, some missed detections were observed, including the dark-colored vehicle shown in the qualitative comparison. Meanwhile, the detector maintained the highest confidence for the most visually salient vehicle in both illumination conditions.

The qualitative observations, confidence statistics, ranking analysis, spatial heatmaps, and exploratory correlation analysis taken together provide complementary information about the effect of illumination on pretrained YOLO11s detections. The results show that YOLO11s provides an effective baseline for lightweight vehicle detection studies under controlled illumination shifts, but also its sensitivity to low-light environments and reduced object-background contrast. These limitations warrant further evaluation on real nighttime scenes and larger datasets before drawing broader conclusions about deployment in Intelligent Transportation Systems and Advanced Driver Assistance Systems.

## IV. CONCLUSIONS

In this paper, a YOLO11s-based vehicle detection framework was proposed to evaluate the detection performance under daylight and simulated night conditions. The framework involves controlled nighttime image simulation, lightweight image enhancement based on CLAHE and Gamma Correction, pretrained YOLO11s vehicle detection, and statistical visualization without model retraining.

The experiments showed that the detection performance is largely degraded when the illumination is decreased, where 10 vehicles are detected under daylight conditions and only 3 vehicles are detected under the simulated nighttime conditions. However, the most visually salient vehicle still received a high confidence score in both conditions. The sensitivity of YOLO11s to reduced luminance and object-background contrast was also shown by the inability to detect some darker or less visually distinct vehicles under simulated nighttime conditions.

Confidence-based analyzes such as descriptive statistics, confidence distributions, detection ranking, scatter visualization, confidence-weighted heatmaps, and exploratory correlation analysis provided complementary insights into detector behavior. The results indicate that the degradation in illumination mainly reduced the number of detectable vehicles, and that larger and more visually salient vehicles generally received higher confidence scores. However, these findings should be treated as exploratory rather than statistically conclusive, as only three nighttime detections were available for correlation analysis.

Overall, the proposed framework offers a simple and reproducible solution to evaluate pretrained YOLO11s under controlled illumination variations. YOLO11s is a useful lightweight baseline for vehicle detection, but its performance limitations under low-light conditions indicate that further validation is needed before it can be practically implemented in ITS and ADAS. Future work should include real nighttime driving data, larger and more diverse datasets, adverse weather conditions such as rain and fog, comparisons with other object-detection architectures, and the use of multi-object tracking.

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